THNN - A Neural Network Model for Telehealth Data Incompleteness Prediction*

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***Abstract*— In modern day medical practices, practitioners and physicians are adapting to new technologies and utilizing new methods of communication with patients. Telemedicine, or telehealth, is one of the newest innovations in medical technology, enabling practitioners to communicate with their patients over the phone, video conferencing, or chat. However, clinical data and sentiments are often not reflected in the practitioner's analysis and diagnosis of the patients they serve. As a solution to the problem of data incompleteness in telehealth, THNN allows medical practices to accommodate for possible missing or incomplete data and provide a greater quality of care overall. Through an ensemble of Natural Language Processing (NLP) and AI-enabled systems, THNN produces sentiment and incompleteness mapping to provide seamless results.**

***Clinical relevance*— The method presented utilizes telehealth natural language data to process the sentiments of patients and the incompleteness found in the conversations, increasing the possibility of improved healthcare outcomes.**

I. INTRODUCTION

Medicine has progressed greatly over the past 20 years, opening new pathways for patient care that were not previously available. Many of these advances include new formulations of medications, the improvements to electronic health record (EHR) systems, and more recently, telemedicine or telehealth. Telehealth practices involve the usage of a phone, computer, or smart device to provide communication between a medical practitioner and the patient, with no need for physical involvement from either party. This has greatly improved the patient's quality of care and allowed for many patients who could not previously access easy and affordable healthcare to have a new option open to them.

Given the rapid advancement of telehealth systems, many have faced some challenges when it comes to patient communication and data loss. Data incompleteness in telehealth is defined as lost or missing data, either from errors in miscommunication, the fast-paced environment, or the limitations of the chat/virtual model.

Based on this fact, the investigators chose to utilize and improve a Natural Language Processing (NLP) model to provide improved patient understanding and a fuller analysis of data incompleteness in medical transcripts.

The specific research objectives in this work are as follows:

1) To propose a novel method of finding data incompleteness in telehealth systems while utilizing an ensemble of NLP and Neural Network models
2) To analyze the sentiments of the patients and find correlations between provider and patient responses
3) To create and form word graphs from responses, allowing for an easier understanding of correlations and sentiments

The authors propose a novel approach to predict the completeness of data in telehealth systems using Telehealth-Neural Network (THNN). The section that follows will explain the rationale behind the methods chosen for this approach.

II. BACKGROUND

A. Data Incompleteness in Natural Language Data

According to Kohane et. al [1], Data Completeness in medical natural language data involves the data quality and representation of the populations in which the medical systems are serving. For this, there were several criterion chosen in the previously mentioned study to allow for a statistically accurate and encompassing measurement be taken. This included descriptions of procedures completed, ICD codes being used correctly in the EHR system, and full and complete patient summary notes.

B. Application of Neural Networks in Natural Language Processing

According to Kuziemsky et. al [2], there are several forms of AI and machine learning methodologies that can be applied to natural language data, and more specifically, onto telehealth data. Currently, many of the use cases for these systems involve the usage of image processing systems, such as those seen in the diagnosing of cancers or melanomas. However, these neural network systems can also be trained on natural language data and be utilized to create sentiment maps for the overall data structure.

According to Meystre et. al [3], a similar system using Neural Networks can be developed and utilized on patient notes with high accuracy, making it clear that diagnosis and treatment through telehealth is not only possible, but high effective. The authors also state that they utilized a multi-layer neural network, which...

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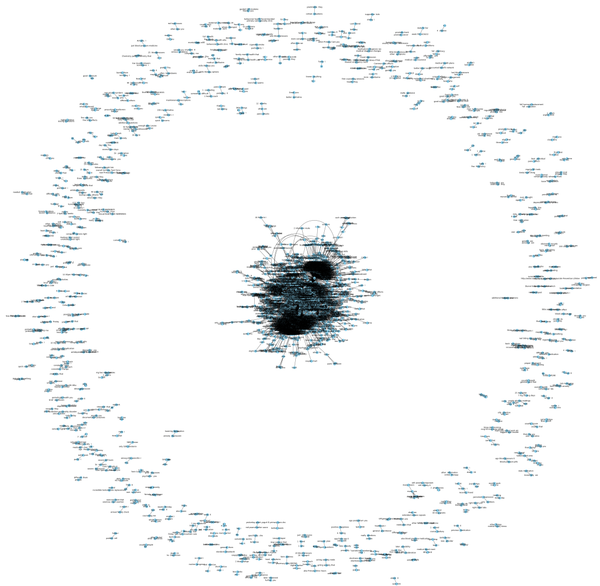


Fig. 1: Directed Word Graph using THNN

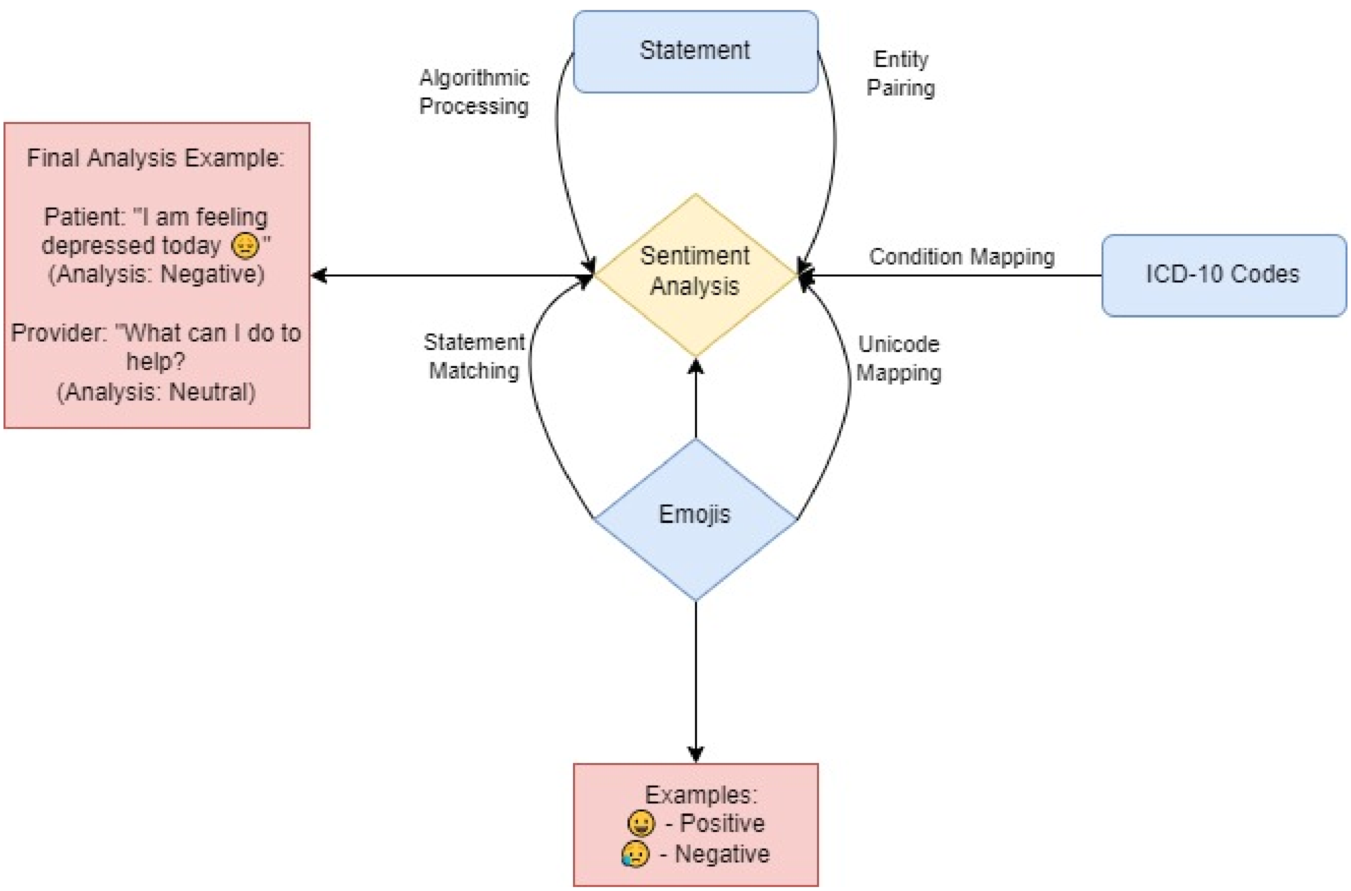


Fig. 2: Causal Connection Diagram for THNN

Algorithm 1: THNN Model

Data: Transcript Data from Telehealth System
Result: Predictions and Sentiments of Patients & Providers
Let n be the layers of the model;
Let X be an empty model of Neural Networks;
Let Y be the set of Identification Categories in TH;
Let Z be the set of Words in TH;
for *each y in Y* **do**
  X.add(layer(n)(y));
end
for *each z in Z* **do**
  X.add(layer(n)(z));
end
for *each h in Y* **do**
  Let s_y = [i is a set instance of Identification Categories in TH — instance(i, h)];
  for *each j is* s_y **do**
    layer(n)(j) $\rightarrow$ layer(n)(h);
  end
  Let s_z = [z is a set instance of words in TH — ValidC(h, z)];
  for *each k is* s_z **do**
    layer(n)(k) $\rightarrow$ layer(n)(h);
  end
  if s_c = *[l is a set instance of Identification Categories in TH — instance(n, l)]* **then**
    layer(n)(h) $\rightarrow$ LSTM;
  end
end
return X;

III. METHODS

A. Mathematical Formulations

In this section, we present a methodology for creating the final neural network model and sentiment functionality for a telehealth chat system, with the given structure assisting in the design and modeling of Recurrent Neural Networks (RNNs). The data collected in each of the categories and words of the telehealth system contain a theoretical weight, allowing the design of the final model to be modeled after a recurrent neural network and NLP-based system.

For this, we define an RNN for the weighted data as the following:

- A space-ordered sequence of arrays and data points
- The arrays and data points contain n values (where values are numbered from 0 up to n values)
- Each value is associated with a weight
- The arrays and data points of n values match with the inputs associated with the data measured at certain weights

This definition of an RNN is adopted from several works on neural networks [4], but does not encompass the definition needed within the telehealth ecosystem.

To reflect these needs, a new definition for an telehealth recurrent neural network (RNN) is as follows:

- A telehealth RNN, F = inputs $[x_1, x_2, ..., x^n]$ and $[h_1, h_2, ..., h^n]$, is a space-ordered sequence of arrays and data points.
- Each point, x_n^{t+1} represents n data values for $t+1$ timestamps for x identification categories in the telehealth system, where the array of hyperedges, $X = [x_1^{t+1}, x_2^{t+1}, ..., x_n^{t+1}]$.
- Each point, $x_n^{t+1} \in \mathbb{R}$, where $\mathbb{R}$ represents the input of all real numbers at time step $t+1$. $y_n^{t+1} \in \mathbb{R}$ represents the output of the hidden layers at time step $t+1$.
- $h_t \in \mathbb{R}^m$ represents the hidden states at time step t.
- $b_h \in \mathbb{R}^m$ represents the bias in the current layers of the neural network.
- $b_y \in \mathbb{R}$ represents the bias in the hidden layers of the neural network.
- Our formal definition of weights is W = $[(w_h, w_x, w_y)|(w_h$ precedes $w_x), w_y, b_x, b_y \subseteq X, w_h \cap w_x = \varnothing]$

B. THNN Algorithm and Explanation

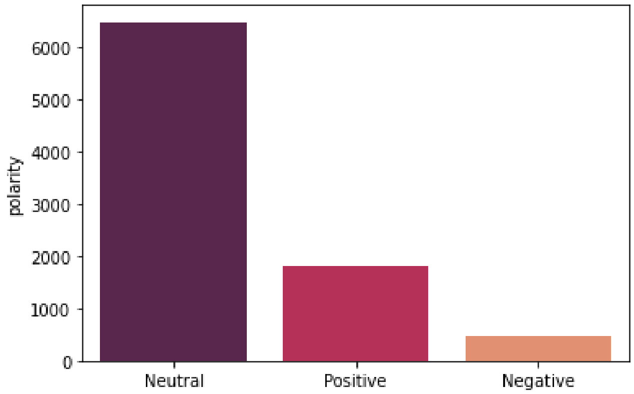
Typically, an average telemedicine system requires simple and easy-to-understand conversations between providers and patients to determine the highest quality of care to the patients and the greatest outcomes for diagnosis and treatment from the end of the providers. This requires that the system is optimized and streamlined on both ends, allowing for secure, end-to-end communications to occur. RNNs can measure data incompleteness and sentiments in both the medical professionals and the patients treated using the system, saving time and energy exerted during analyses of the systems.

Given how these systems operate, we propose an ensemble procedure of natural language and recurrent neural network systems to determine the true sentiments of the patients and providers, while also providing a final measure of incompleteness across the board.

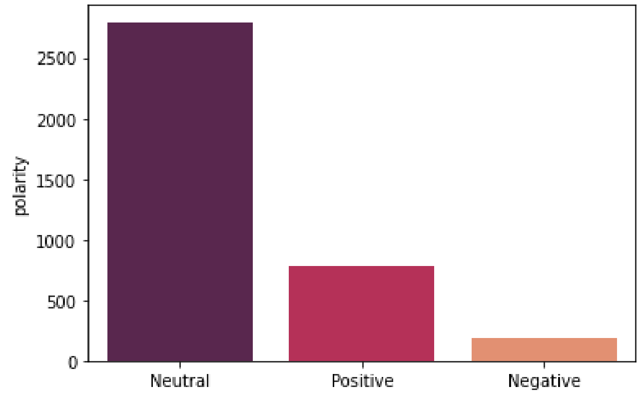
To do this, we also propose a series of definitions to define how the structure of the system is utilized in the algorithm.

- Each telehealth system includes several different categories and dictionaries of words where information is stored, where the output in categories depends on the input from the dictionaries, and each category has multiple dictionaries. These dictionaries contain a hierarchy of how they are stored, and their respective data.
- Measures are taken for all of the data in each of the dictionaries, include occurrences and datatypes.
- Dependencies are measured in *occurrences*.
- *IC* identifies identification categories, and *sentiments* identifies sentiment completeness and availability of data in the dictionaries identified by the algorithm.
- *words* represents the data measured for each data point in the telehealth system.

The methodology proposed follows a typical telehealth architecture and goes through the system, checking for data incompleteness as:



(a) Polarity of Training Set following Sentiment Analysis



(b) Polarity of Test Set following Sentiment Analysis

Fig. 3: Polarity of Test and Training dataset following Sentiment Analysis

1) Identify the categories of a telehealth system and subsequent hierarchical dependencies (*instances(**category0, category1**)*)
2) Identify the dictionary of each indexed category (*IC(**category0, dictionary1**)*)
3) Identify whether the dictionaries have complete datasets (*sentiments(**dictionary0, data1**)*)
4) Identify the completeness of the dataset in the dictionaries (*words(**data0, data1**)*)

By applying these stages and steps through the methodology, the process for finding incomplete data becomes much faster and has higher predictability.

IV. RESULTS

To show the practicality and use of the THNN model, tests were done on several different conversations to measure data incompleteness, where the goal was to properly predict when a sentiment may be left incomplete or incorrectly responded to and what tends to be the most incomplete within the set of conversations.

A. Preprocessing and Data Incompleteness Analysis

The dataset utilized by the researchers contained 84 unique conversations, with a total of 6,259 sentences or lines. These conversations ranged in tone, with some focused more-so on psychiatry and others on hypertension. A few themes carried over between these conversations, including the usage of ICD-9 & ICD-10 codes, similar openings from the physicians, and a clinical summary note for all patients.

Preprocessing was done on the dataset to ensure that a proper analysis was complete; the following was done during the preprocessing stages:

- The dataset was cleaned for any missing or misidentified identifiers.
- The dataset was split into test and train datasets to train the model on.
- The model was then trained using the training set, with the test dataset being used to determine the accuracy of the sentiments captured by the analysis.
- Further processing was done to the NLP model, where a dictionary was created and used to keep track of all the phrases used by both parties.

B. Evaluation of THNN

The model proposed in this paper, THNN, was tested using an ensemble of methods. The first was an incompleteness test, otherwise known as a Kolmogorov-Smirnov test. This test allows us to see the goodness of fit of a model on the points given, which in this case would coincide with the data incompleteness measures. This was done using the "statsmodel" package, with the authors utilizing a variety of different models to compare to the Kolmogorov-Smirnov test.

The next test done on the model was a sentiment analysis, utilizing NLP matching and testing to see whether or not sentiments matched together from patients and providers. For this, the package "haystack" was used, allowing for statements and phrases to be matched together following a split for testing and training sets.

As a result, the model recorded that patients were overall more positive than providers, and that the providers tended to be more neutral in response to positive or negative sentiments from the patients. About 500 unique statements from the 6,259 statements or phrases were found to be mismatched and that the sentiments of the respondents did not always match those that were being originally told. To further test the findings, the authors chose to run a Chi-Square Test to see where the differences were between patients and providers.

V. CONCLUSION

In this paper, we presented a methodology and proposed a model to utilize the layers of an recurrent neural network for predicting where data may be incomplete in a telehealth system and have a greater understanding of sentiments in patient-provider communications. We introduced our model, THNN, as a method to predict and classify missing data. As a result, we demonstrated that such a concept has the potential to be utilized and implemented in telehealth systems and provide sentiment analysis. In the future, we seek to optimize and identify techniques for implementing such an algorithm in a real-world situation, along with researching the integration of the system with an AI-enabled chat feature.

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